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Passive envelope design optimization of residential buildings using NSGA-II in different Algerian climatic zones

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Abstract

The most sustainable building operation is that presents a minimum primary energy consumption, which minimizes the environmental impact. Therefore, the objective of this paper is to optimize the passive envelope design of the multi-family apartment building in Algeria for reducing heating and cooling energy consumption. 12 representative cities are investigated and 20 design variables with their different combinations are simulated. A multi-objective non-dominated sorting genetic algorithm (NSGA-II) is coupled with EnergyPlus building energy simulation software to obtain the optimal solution according to the Pareto approach. Our optimization approach achieved energy saving ranging from around 21% to 51%.

Key Innovations

- Using an advanced simulation approach involving automated optimization (NSGA-II) and applied for the first time, in the Algerian context.
- Coupling the building performance simulation of a multizone model with a state-of-the-art optimization algorithm.
- Providing an evidence-based design decision support for professionals and policymakers.

Practical implications section added

- Calibrate the building simulation model before optimization.
- Before the parametric simulation, Check carefully for the variable's settings in the Idf editor of EnergyPlus.
- Promote the discrete type for the design variable to allow a faster convergence of the optimization algorithm. In Addition, the adoption of discrete variables is more realistic.

Introduction

Passive design measures such as the building layout, building form, building envelope thermophysics, infiltration & air-tightness can make great contributions to low energy building designs depending on climatic conditions (Chen et al., 2018) (Gou et al., 2018). Therefore, the energy efficiency can be achieved by making early architectural design decisions that integrating the optimal values of these building parameters (Ekici and Aksoy, 2011; Yıldız and Arsan, 2011). However, the number of parameters that can affect the building energy consumption is rather huge, and different parameters are often in contrasting influences. This huge number of building parameters involves the largest number of design possibilities which should be considered by designers. Therefore, to achieve an optimal design solution in this situation building energy performance simulations are required. But this method involves complex processes, can be expensive, and time-consuming, because it requires running a large number of simulation cases (Attia et al., 2012; Gou et al., 2018; Huang and Niu, 2016). Hence, optimization methods use become necessary to get an optimal passive design solution among a number of potential combinations of various variables and enhance significantly the building energy performance.

So, Building Performance Optimization (BPO) is a process that aims at the selection of the optimal solutions from a set of design possibilities according to a set of performance criteria (e.g. minimization of energy demand, maximization of indoor comfort,…) (Attia et al., 2013). Recently, this process is usually automated by the coupling between a building simulation program and an optimization 'engine' which may consists of one or several optimization algorithms or strategies (Nguyen et al., 2014). This new process is called Building Energy simulation and Optimization (BESO).

The major part of previous studies is based on Building Energy Simulation and Optimization (BESO) where they coupled simulation tool or prediction model with optimization algorithms. The Genetic Algorithm (GA) or its variations such as Non-dominant Sorting Genetic Algorithm (NSGA) are the most used in simulation-based design for building envelope optimization which is confirmed by Huang and Niu (2016), Machairas et al. (2014a), Nguyen et al.(2014)and Shi et al. (2016).

In the Algerian context, we found many studies presented an evaluation of one or some design variables or passive design strategies in one ore some climate zones to optimize the building energy consumption or improve indoor thermal comfort (Hamdani et al., 2014; Imessad et al., 2014; Ali-Toudert and Weidhaus, 2017 ; Mokhtari et al., 2017; Berghout and Forgues, 2019; Rahmouni and Smail, 2019; Soufiane et al., 2019; Badeche and Bouchahm, 2020).

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Based on the previous literature all studies used a parametric simulation method to optimize the building design. This method is simple to be carried out, however it is often time-consuming and results in partial improvements (Gou et al., 2018; Machairas et al., 2014a). Previous studies evaluated the effect a few design variables. In addition, they investigated between one and three locations or climate zones in Algeria. Also, none of those studies used Building Energy Simulation and Optimization (BESO) approach, which combines the simulation tool or prediction model with optimization algorithms.

In the above discussed panorama, our study aims to investigate the influence of the multi-family apartment building characteristics on the definition of optimal passive and energy efficiency solutions considering heating and cooling energy performance across the Algerian territory (12 different representative cities cover all Algerian climate zones). A genetic algorithm in combination with a simulation tool is used to investigate the most promising design strategies able to optimize the energy performance according to the Pareto approach. A wide range of conventional passive and energy efficiency measures (20 design variables), not including building geometry or occupant adaptation, have been considered in order to maximize the building energy performance for each climate zone.

Methods

The research methodology is based on a comparative approach to the energy loads of the optimized building model with the reference building model for a real-world reference case. The methodology of this study followed a four-stepped approach (see Figure 1). Each step is described in detail in the following sections.

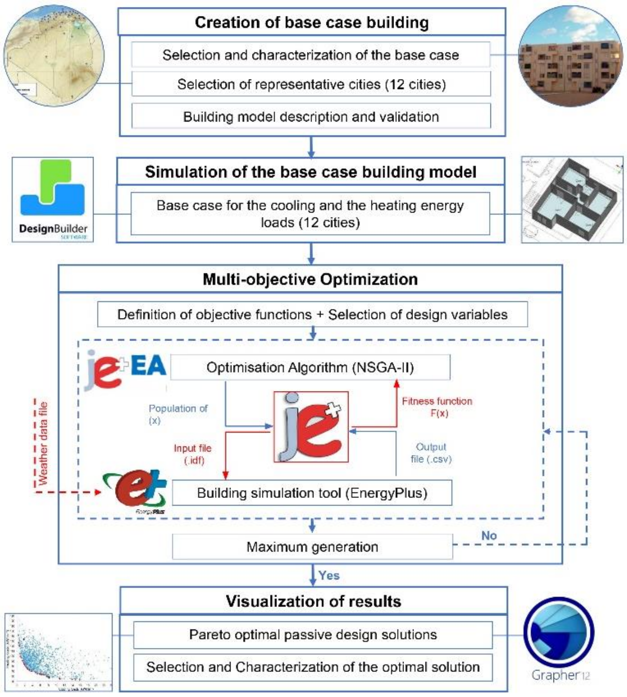

Figure 1: Study conceptual framework

- Creation of base case building:

The selected building model represents a typical multi-family social residential building which is the most common typology in Algeria (Semahi et al., 2019). The study of Semahi et al. (2020) proved the representability of the chosen typology (see Figure 2).

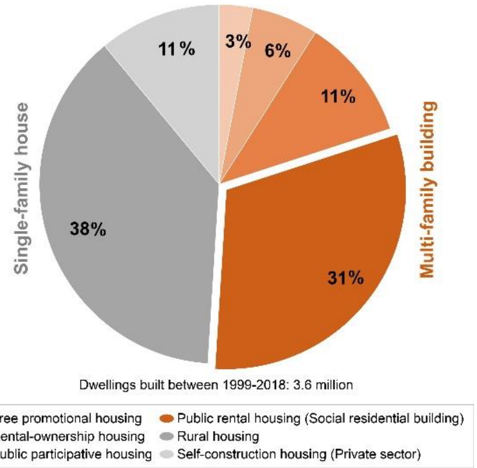

Figure 2: Characterization of residential housing typologies in Algeria

The constructional details, the geometrical design of the representative dwelling (see Figure 3), and the thermophysical properties of the building elements is shown in Semahi et al. (2019). Table 1 summarizes the construction properties and thermophysical properties of the building elements according to a walkthrough audit and in compliance with the Algerian Thermal Regulation of Residential Buildings

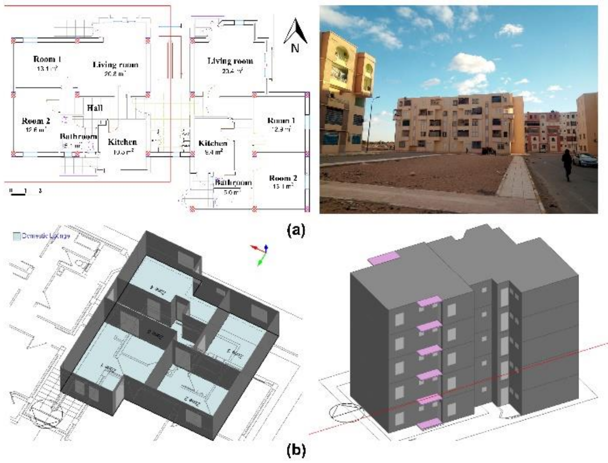

Figure 3: Details of the selected multi-family social housing building typology; (a) real view and floor plan of the base case building, (b) simulated building model developed in DesignBuilder (EnergyPlus)

The reference building was modeled using EnergyPlus v.9.1.0 software. The building model is calibrated under hourly and monthly data through winter and summer indoor temperature and electricity and gas use. The monitoring, the calibration and validation process of model accuracy is described in detail in Semahi et al. (2019).

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Table 1: Thermal properties of the building elements of the selected multi-family social housing typology

N°	Building element	Outside to inside	Composition	Thickness (m)	Thermal conductivity (W/m-K)	Density (kg/m3)	Specific heat capacity (kJ/kg K)	U-value (W/m2-K)
1	Exterior wall	Layer 1	Mortar	0.02	1.15	1900	1.08	1.118
		Layer 2	Hollow brick	0.15	0.48	900	0.93	
		Layer 3	Air cavity	0.05	0.024	1.22	1.00	
		Layer 4	Hollow brick	0.1	0.48	900	0.93	
		Layer 5	Plaster	0.02	0.35	800	0.93	
2	Partition wall	Layer 1	Plaster	0.02	0.35	800	0.93	1.857
		Layer 2	Hollow brick	0.1	0.48	900	0.93	
		Layer 3	Plaster	0.015	0.35	800	0.93	
3	Internal floor	Layer 1	Tiling	0.02	1.7	2200	0.93	1.985
		Layer 2	Mortar	0.03	1.15	1900	1.08	
		Layer 3	Concrete slab	0.2	1.45	1450	1.08	
		Layer 4	Plaster	0.02	0.35	800	0.93	
4	Roof	Layer 1	Tightness	0.015	0.7	2100	1.04	0.584
		Layer 2	Mortar	0.04	1.15	1900	1.08	
		Layer 3	Polystyrene	0.05	0.04	20	1.4	
		Layer 4	Concrete slab	0.2	1.45	1450	1.08	
		Layer 5	Plaster	0.02	0.35	800	0.93	
5	Ground floor	Layer 1	Concrete	0.1	1.75	2500	1.08	3.259
		Layer 2	Mortar	0.03	1.15	1900	1.08	
		Layer 3	Tiling	0.02	1.7	2200	0.93	

All Algerian climatic zones were included in this study. Therefore, and based on the new climate classification created by Semahi et al. (2020), we selected twelve (12) representative cities (see Figure 4): 6 cities represent 6 zones for cooling and heating energy loads, 3 other cities represent 3 zones for cooling energy loads only, and 3 other cities represent 3 zones for heating energy loads only.

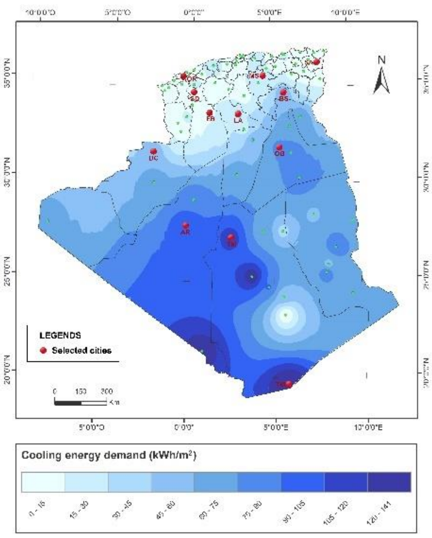

Figure 4: Selected representative cities

- Simulation of the base case building model:

To establish a reference case for the cooling and the heating energy demands, the calibrated model of the base case developed previously is simulated using EnergyPlus 9.1.0 software. It is important to notice that natural ventilation is used to cool down the dwelling if the indoor temperature is higher than 21.2 °C (it was assumed that 21°C is heating set point) and lower than 26.8 °C (it was assumed that 27°C is cooling set point), the outdoor temperature should be between 18 °C and 26 °C, and the outdoor temperature should be less than the indoor temperature (Grygierek and Ferdyn-Grygierek, 2018; Lapisa et al., 2018). The latest version of the Typical Meteorological Year (TMY3) hourly weather data files for the twelve selected cities was used (Lawrie and Crawley, 2019).

- Multi-objective optimization approach:

The first step in this section was the definition of the objective functions. Algeria has two contrasting regions. Heating-dominated region in the Centre and cooling dominated regions in the South. Therefore, the number of indoor discomfort hours during summer and winter are important, as well as the cooling and heating energy demands. The objective is the minimization of the energy required by the cooling and heating system. Two objective functions are used and are described as follows:

$$\text{Min } f_1(\bar{x}), f_2(\bar{x}), (\bar{x}) = [x_1, x_2, \dots \dots \dots \dots, x_{20}] \quad (1)$$

f_1: represents Qcool which is the annual cooling demand of building.

f_2: represents Qheat which is the annual Heating demand of the building.

The energy demand for lighting, domestic hot water systems, cooking, appliances were not taken into account in this study.

The second step in the optimization section is the selection of design variables. Design variables represent elements which are modified during the optimization process. The selected design variables include several early-design phase decisions. 20 design variables are selected and they are encoded by the vector (X) (Table 2).

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We selected some variables like packages which cover many proprieties of the same element simultaneously. These variables are into the discrete type, which allows a faster convergence of the optimization algorithm. Moreover, the adoption of discrete variables in our case is more realistic, because we selected the design solutions and their variations from the Algerian thermal regulation (DTR C3-2) for residential buildings (CNERIB, 1997).

The discrete selected variables are the block thermal conductivity/density of the external wall (Table 3), the block thermal conductivity/density of the floor and the roof (Table 4), the insulation type of the external wall, roof and floor (Table 5) and the window type (Table 6). The rest of the variables are continuous uniform. All these variables were created in the idf file using idf Editor of EnergyPlus.

Table 2: Characterization of design variables

Design variables	Options Unit	Variables number	Variables type	Lower and upper bounds	Variation step	Ref. value
Building orientation	(°)	X_1	Continuous uniform	[0,345]	15	0
Block thickness for the external walls	(m)	X_2	Continuous uniform	[0.075, 0.25]	0.025	0.15
Block thickness for the floor	(m)	X_3	Continuous uniform	[0.12, 0.25]	0.04	0.16
Block thickness for the roof	(m)	X_4	Continuous uniform	[0.12, 0.25]	0.04	0.16
Block thermal conductivity/density of the external wall	(W/m-K) (Kg/m3)	X_5	Discrete	[EW1, EW6]	(Table 3)	EW2
Block thermal conductivity/density of the floor	(W/m-K) (Kg/m3)	X_6	Discrete	[F1, F4]	(Table 4)	F3
Block thermal conductivity/density of the roof	(W/m-K) (Kg/m3)	X_7	Discrete	[R1, R4]	(Table 4)	R3
Insulation thickness of external wall	(m)	X_8	Continuous uniform	[0, 0.09]	0.01	0
Insulation thickness of the floor	(m)	X_9	Continuous uniform	[0, 0.09]	0.03	0
Insulation thickness of the roof	(m)	X_{10}	Continuous uniform	[0, 0.09]	0.03	0
Insulation type of external wall	(-)	X_{11}	Discrete	[I1, I4]	(Table 5)	I3
Insulation type of the floor	(-)	X_{12}	Discrete	[I1, I4]	(Table 5)	I3
Insulation type of the roof	(-)	X_{13}	Discrete	[I1, I4]	(Table 5)	I3
Solar absorptance of the external walls	(-)	X_{14}	Continuous uniform	[0.1,0.9]	0.05	0.6
Solar absorptance of the roof	(-)	X_{15}	Continuous uniform	[0.1,0.9]	0.05	0.85
Living room window to wall ratio	(%)	X_{16}	Continuous uniform	[10,60]		11.47
Bedroom window to wall ratio	(%)	X_{17}	Continuous uniform	[10,60]		12.78
Window type	(-)	X_{18}	Discrete	[W1, W15]	(Table 6)	W2
Living room overhang depth to window height ratio	(-)	X_{19}	Continuous uniform	[0,1]	0.05	0
Bedroom overhang depth to window height ratio	(-)	X_{20}	Continuous uniform	[0,1]	0.05	0

Table 3: Block thermal conductivity/density of the external wall (DTR3-2) (CNERIB, 1997)

N°	Wall material	Thermal conductivity (W/m-K)	Density (kg/m3)	Specific heat capacity (J/kg K)
EW1	Aerated concrete	0.33	750	1080
EW2	Burned clay hollow brick	0.48	900	930
EW3	Concrete hollow brick	0.65	1300	1080
EW4	Sand-lime brick	0.8	1600	930
EW5	Compressed Stabilized Earth Blocks	1.15	2000	936
EW6	Concrete	1.75	2500	1080

Table 4: Block thermal conductivity/density of the Floor/Roof (DTR3-2) (CNERIB, 1997)

N°	Floor/Roof material	Thermal conductivity (W/m-K)	Density (kg/m3)	Specific heat capacity (kJ/kg K)
F1/R1	Expanded Polystyrene Hollow block	0.23	830	1290
F2/R2	Burned clay hollow block	0.48	1700	930
F3/R3	Concrete Hollow block	0.65	2000	1080
F4/R4	Concrete	1.75	2500	1080

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Table 5: insulation types (DTR3-2) (CNERIB, 1997)

N°	Insolation type	Thermal conductivity (W/m-K)	Density (kg/m3)	Specific heat capacity (J/kg K)
I1	Polyurethane Foam	0.031	35	1404
I2	Glass wool/fiber	0.034	45	612
I3	Expanded Polystyrene (EPS)	0.04	15	1404
I4	Stone Wool	0.047	21	612

Table 6: Window types

N°	Type	Description	U-value (W/m2 K)	T-value	SHGC
W1	Single glazing	Clear, Low iron, 3mm	5.89	0.89	0.9
W2		Clear, 6mm	5.77	0.77	0.81
W3		Clear, Reflective-D, 6mm	5.72	0.4	0.5
W4		Clear, Reflective-B-H, 6mm	5.06	0.24	0.4
W5		Clear, Reflective-A-H, 6mm	4.97	0.16	0.32
W6		Clear, Reflective-A-L, 6mm	4.44	0.06	0.2
W7	Double glazing	Clear, Low iron, 5mm/13mm, Air	2.68	0.79	0.81
W8		Clear, 6mm/13mm, Air	2.66	0.6	0.7
W9		Clear, Reflective-D, 6mm/13mm, Argon	2.49	0.34	0.42
W10		Clear, Reflective-B-H, 6mm/13mm, Air	2.44	0.19	0.3
W11		Clear, Reflective-B-L, 6mm/13mm, Air	2.42	0.12	0.22
W12		Clear, Reflective-A-L, 6mm/13mm, Air	2.21	0.05	0.13
W13	Triple glazing	Clear, Low-e Film (55), 6mm/13mm, Air	1.2	0.21	0.31
W14		Clear, Low-e (e2=e5=0.1), 3mm/13mm, Air	0.98	0.35	0.47
W15		Clear, Low-e (e2=e5=0.1), 3mm/13mm, Argon	0.78	0.35	0.47

For the third step which represents the selection of the Optimization algorithm. We used a multi-objective approach based on the implementation of a genetic algorithm (NSGA-II). GA represents the most popular evolutionary algorithm used in optimization and the version NSGA-II is more suitable to solve multi-objective optimization problems, which are common in architecture (Ascione et al., 2019b; Hamdy and Mauro, 2017; Machairas et al., 2014).

In this study, the NSGA-II input parameters were selected according the following values (Table 7) based on Ascione et al. (2019a), and (2019b). The evolution of population will stop once the maximum number of generations is reached. In our case, the maximum number of iterations calculated by the NSGA-II is equal to 2400 iterations.

Table 7: NSGA-II input parameters

NSGA-II parameter	Value
Population size	80
Maximum generation number	30
Crossover fraction	0.6
Mutation probability	0.1
Elite count	2
Tolerance value	0.001

The optimization is conducted using EnergyPlus coupled with jEPlus+EA (Zhang, 2012).jEPlus can automatically change the variables values in building simulation model and call EnergyPlus to do the building performance simulation (Li et al., 2018). Also, jEPlus+EA allows converting the output file of EnergyPlus (.csv) into the vector of the objectives (F) (Figure 1).

- Visualization of results:

To visualise the optimization results the Pareto front was used. Pareto front represents the popular approach for multi-objective optimization when there is more than one objective function for optimization which is common in building design problems and these functions are often contradictory (Machairas et al., 2014).

In this study we decided to visualize only the annual heating and cooling energy demand on a scatter plot diagram. The final optimal solution in our case represents the optimal solution for both objective functions simultaneously.

To select the final optimal solution out of the best solutions of the Pareto Front, we calculated the distance of the Pareto optimal solutions to the "ideal point" (Pideal), which is defined as the set of the best solutions to each independent problem (cooling and heating energy demand in our case) (Bre and Fachinotti, 2017; Li et al., 2018). Pideal = [Min (f_1) Min (f_2)] (2)

To calculate the distance of a Pareto optimal solution (Popt) to the ideal point we used the following equation:

$$\mathrm{d(Popt)} = \sqrt{[f_1(\mathrm{Popt}) - \min(f_1)]^2 + [f_2(\mathrm{Popt}) - \min(f_2)]^2} \quad (3)$$

The final optimal solution (Popt) is defined as that Pareto optimal with the shortest distance to the ideal point (Bre and Fachinotti, 2017; Ehrgott and Tenfelde-Podehl, 2003). The selected optimal solution will be compared

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with the reference case to evaluate the improvement regarding the annual heating and cooling energy demand.

Results

Based on the number of variables, the combination of all options result in a solution space composed of 1.19 E+18 possible solutions. Each building simulation run can take 1.5 min in average with EnergyPlus software. Therefore, to explore this huge solution space it would require a computational time around 3.3 E+12 years, which is not feasible. For this reason, only 2400 energy simulations are run for each location using genetic algorithm (GA) to perform the evolution of a starting population of 80 individuals for 30 generations. Thus, the optimization process can be feasible. The total simulation time of these 2400 cases was around 60 hours for each location using a processor Intel® Core™ i5-2430M CPU at 2.40 GHz. The total simulation time of all locations was around one month. The results of the optimization process are reported in the form of Pareto Front for 12 selected representative cities (see Figure5 and Figure 6 as examples). The optimization results are divided into two main categories, heating-dominated cities and cooling-dominated cities:

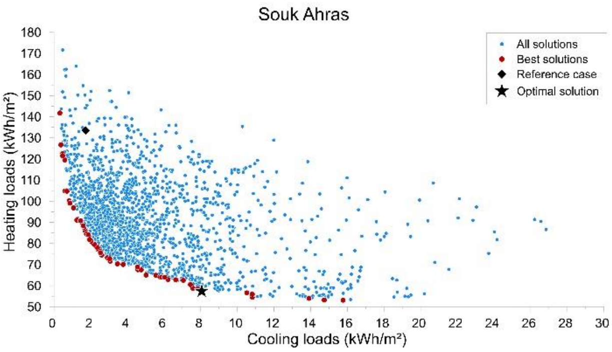

Figure 5: Pareto fronts for Souk Ahras (example of heating-dominated cities)

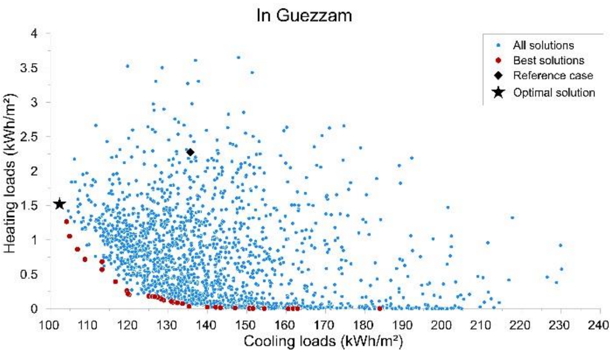

Figure 6: Pareto fronts for In Guezzam (example of cooling-dominated cities)

In the heating-dominated cities, the heating energy loads of optimal solution varies annually from 25.33 kWh/m2 (Oran) to 57.40 kWh/m2 (Souk Ahras), with reduction of 33.39 kWh/m2 (54.5%) and 76.11 kWh/m2 (57%), respectively. Also, the cooling energy loads varied annually from 8.05 kWh/m2 (Souk Ahras) to 36.29 kWh/m2 (Laghouat), with an increase of 6.32 kWh/m2 (13%) and 4.19 kWh/m2 (around 365%), respectively.

In the cooling-dominated cities, the cooling loads varied from 53.01 kWh/m2 (Bechar) to 102.33 kWh/m2 (In Guezzam), with reduction of 3.88 kWh/m2 (around 7%) and 33.27 kWh/m2 (around 27.5%) respectively. Also, the heating loads varied from 1.51 kWh/m2 (In Guezzam) to 20.39 kWh/m2 (Bechar), with reduction of 0.76 kWh/m2 (around 33.5%) and 21.77 kWh/m2 (around 51.5%) respectively.

Our results indicate that our optimization is very effective for reducing the heating loads in the heating-dominated cities, despite, the slight increase in the cooling loads. However, the results indicate that our optimization is less effective on cooling and heating loads in the cooling-dominated cities (see Figure 7).

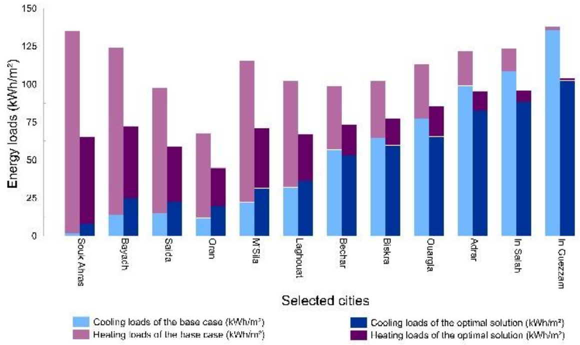

Figure 7: Annual cooling and heating energy loads of the optimal solution compared to the base case for selected representative cities

Discussion

- Summary of main findings:

The current base case that represents the most commonly constructed architectural type in Algeria is far away from the optimal design recommendations provided in this study.

Our optimization approach achieved energy saving ranging from around 21% to 51%. For heating dominated cities like Souk Ahras, Bayadh, M'Sila: the energy saving rate is between 33% and 51%. For cooling dominated cities like Ouargla, Adrar, In Guezzam: the energy saving rate is between 21% and 25%. The optimization results prove that the solution sets are effective within each city.

- Strength and limitations:

In this research, an advanced simulation approach involving automated optimization (NSGA-II) was used and applied for the first time, in the Algerian context. There are several previous studies that conducted parametric analysis to improve the energy efficiency of buildings in cities in the arid or temperate climate of Algeria (Ali-Toudert and Weidhaus, 2017; Fezzioui et al., 2009). However, most of those studies explore improvement opportunities using manual approached resulting into limited solution spaces and sub-optimal results. Thus, this study is one of the first studies that apply automated optimization of passive design measures for a mainstream building typology, in Algeria. The extensive evaluation of all the possible combinations of passive and energy efficiency through the NSGA-II, achieved remarkable results in an acceptable computation

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time budget. The application of optimization techniques allowed us to perform an accurate analysis of the entire dimension of the energy efficiency problem while condensing considerably the sets of recommendations with evidence-base content.

North African cities are booming and are increasingly urbanized. Therefore, this work provides evidence-based design decision support for professional and policy makers in Algeria. The base case in a monitored and calibrated reference case that represents a mainstream typology based on-site audits for local materials and building construction technology. Coupling the building performance simulation of a multizone model with state-of-the-art optimization algorithm (advantages of NSGA-II) brings valuable insights on the design improvement opportunities for new construction and renovation opportunities for existing building types.

It is acknowledged that the study applied a genetic algorithm for multi-objective optimization with a focus on energy use reduction. The research could have benefited from a broader approach that involve comfort and cost as objectives. However, the complexity and findings abundance, forced the authors to focus on one objective as an important milestone. Thus, further investigation should address multiple objectives. Also, the study has been focused on residential buildings without considering possible adaptation of occupants. In this way, the study was mainly based on adopting the variables identified by the Algerian thermal regulation (DTR C3-2) that mainly address the envelope's thermal performance and surfaces orientation (CNERIB, 2007). Thus, the study succeeded to define key passive and energy efficiency measures of the envelope that must be improved. However, it did not address retrofit opportunities or optimal comfort adaptations. Further investigations will be carried out in order to evaluate the influence of occupants' adaptation on comfort, cost and carbon optimal solutions.

- Implication on practice and research:

The research findings can help with the modification of the Algerian building thermal standard through the Ministry of housing (MHUV) or the CNERIB.

For building professional and on the scale of individuals, our findings can inform and guide the decision making of architects and building engineers. Real estate developers can benefit from the results and develop of feasible and energy efficient prototypes. An in-depth study will be the following future work for the authors to fully investigate the other passive design strategies (heating and cooling), including natural light and occupant/thermal adaptation aspects of the building as a whole. Also, we believe that this research is the foundation of future studies that can couple our reference case with other solutions packages including HVAC systems and renewable energy systems to reach nearly zero energy buildings (Attia, 2018).

Conclusion

In this study, a reference building has been analysed. The aim of study is investigating the influence of the multi-family apartment building characteristics on the definition of optimal passive and energy efficiency solutions considering heating and cooling energy performance. A genetic algorithm coupled with a simulation tool is used to investigate the most promising design strategies able to optimize the energy performance according to the Pareto approach. Conventional passive and energy efficiency measures, not including building geometry or occupant adaptation, have been considered in order to maximize the building energy performance. The major research findings were as follows:

- In heating dominated cities, the optimization of the envelope physio-thermal properties can lead to the reduction of heating energy loads up to 55% (equivalent to 30-76 kWh/m2) annually.
- In cooling dominated cities, the optimization of the envelope physio-thermal properties can lead to the reduction of cooling energy loads up to 24% (equivalent to 4-31 kWh/m2) annually.
- Overall, the optimization passive and energy efficiency measures for building envelopes is more effective in heating dominated cities and can achieve remarkable energy use savings.

The application of passive and energy efficiency measures for new and existing multi-family apartment buildings in North Africa region can significantly attenuate building energy use that occurs in most energy-intensive households.

Future work will focus on predicting building energy consumption without simulation and optimization which are complicated issues for architects. The development of prediction models represents a design decision support which could be potentially helpful for architects and engineers in the early design and construction stages.

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